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Research article

Willingness to pay for protection from storm surge damages under climate change in Halifax Regional Municipality

Patrick Withey[a,*], Deny Sullivan[a], Van Lantz[b]

[a] Department of Economics, St. Francis Xavier University, Antigonish, NS, B2G 2W5, Canada
[b] Faculty of Forestry and Environmental Management, University of New Brunswick. 3 Bailey Dr, Fredericton, NB, E3B 5A3, Canada

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ABSTRACT

Climate change poses risks to coastal cities due to sea-level rise and changes in storm surge. Using the contingent valuation method and payment card format, this paper seeks to estimate residents of Halifax Regional Municipality's willingness to pay (WTP) for protection from flooding impacts from storm surge. The contribution of this study is the application of this method in a previously unstudied region, to understand individuals' perception of risk and WTP to avoid damage, in order to inform policy aimed at protecting against damage due to sea-level rise and storm surge. WTP is estimated without and with the expectation of future climate change, and also for public vs. private goods. Data is analyzed and compared using OLS, Heckman two-step and Tobit Interval regression models. Results suggest that on average, WTP is roughly $12 per month per household over a ten-year period without the expectation of climate change, and roughly $13 per month per household assuming climate change will have negative impacts in the region. Individuals are most often willing to pay to protect against damages to public infrastructure, as well as power outages. Income and education do not play a major role in individuals WTP. Vulnerability to flooding and level of concern related to risky events have a statistically significant impact on WTP in all models, and gender and age have an impact on WTP in some models.

1. Introduction

Climate change is predicted to have significant impacts in the coming decades, and coastal cities are particularly vulnerable to flooding due to climate change. The flood-related effects of climate change in coastal communities are typically due to sea-level rise (SLR) and storm surge. Global average SLR is predicted to increase by as much as 1 m by 2100, in some climate scenarios (Church and Clark, 2013). It is more difficult to predict the impact of climate change on storm surge, although it is generally believed that climate change will result in increased frequency and severity of coastal storm surge, particularly considering rising sea levels (IPCC, 2007, 2013).

Halifax Regional Municipality (HRM), the capitol of Nova Scotia, Canada, has historically been vulnerable to storm surge impacts, given its location in the North Atlantic Ocean.

The goal of this paper is to estimate the willingness to pay (WTP) among residents of HRM to protect against flooding impacts from coastal storm surge in HRM, to inform adaptation policy in this region. There is increasing interest in modeling damages due to climate change worldwide, as well as how to evaluate adaptation options. Several studies have examined the global impact of climate change (Stern, 2007; Tol, 2002, 2009), and many other studies also examined the impact of SLR and the net benefits of adaptation in coastal regions using cost-benefit analysis (Yohe and Schlesinger, 1998; Fankhauser, 1994) or computable general equilibrium modeling (Darwin and Tol, 2001; Withey et al., 2016).

Many recent studies have examined the benefits of mitigation via the WTP for flood protection. Bin et al. (2008) and Bin and Landry (2013) estimated the value of protection from coastal flooding via the change in flood risk premiums using the hedonic pricing method. Many other studies used the contingent valuation method (CVM) to examine the WTP for ecosystem services such as flood protection from wetlands (Brouwer and Bateman, 2005; Farber, 1987; Costanza et al., 2008; Brouwer et al., 1999). The CVM has also been used to directly estimate individual's WTP to protect against flooding. However, as noted by Daun and Clark (2000), there are relatively few applications of CVM to flood risk mitigation (Thunberg, 1988; Clark et al., 2002), and this is particularly true in the context of climate change. There are an increasing number of recent studies that have used CVM to estimate the value of water management and flood mitigation (Navrud et al., 2012; Markantonis et al., 2013; Brouwer et al., 2009; Ghanbarpour et al., 2014; Tapsuwan et al., 2018), including a few examples in the

* Corresponding author.
E-mail address: pwithey@stfx.ca (P. Withey).

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developed world that are particularly relevant to the current study.

Zhai et al. (2006) examined WTP for protection from flooding in at-risk regions of Japan using the payment card format. They determined respondent's WTP to achieve increased risk reduction through various water management tools (levees, sewer upgrades etc.). Understanding such water management tools, as well as water treatment options has been the focus of recent study in many areas (Kim et al., 2018; Sepehri and Sarrafzadeh, 2018). Zhai et al. (2006) found that average WTP is between roughly $C45-75 per year (converted to 2016 dollars) and that flood experience, distance from the river, and income per capita of the region impacted WTP. Ng and Mendelsohn (2006) used CVM and travel cost methods in Singapore to value the protection of beaches, marshes and mangroves. They asked individuals to state their WTP for 50 and 100% protection, and found that individuals were willing to pay $23USD per year for 50% protection and $33USD for 100% protection.

In the Netherlands, Botzen et al. (2009) estimated homeowners WTP for specific climate change mitigation options, whereas Botzen and van den Bergh (2012) estimated WTP for flood insurance, given low probability but damaging flooding events, and climate change. In the survey that is used for both studies, the payment card format was used, and homeowners were initially asked what they are willing to pay for insurance for floods that occur every 1250 years on average (1–1250 year storms). All smaller floods would be protected through established infrastructure. The authors proposed a doubling (and tripling) of flood probabilities due to climate change, so that protection is necessary for 1–600 year and 1–400 year floods, respectively. Overall, for those willing to insure, WTP ranged between 7.85€ and 12.90€ per month, depending on scenario (Botzen and van den Bergh, 2012).

The current study follows this line of research, developing a CVM survey to illicit individual's WTP for protection from coastal storm surge in the HRM region. The survey design follows most closely Botzen and van den Bergh (2012), using the payment card method and examining WTP for full protection from flooding due to storm surge, while increasing the risk of surge due to climate change. However, the key differences are that in this paper protection is considered via theoretical government programs, and not private insurance, and this study also consider how individuals are willing to pay to protect public vs. private goods. OLS, Heckman two-step and Tobit Interval models are used and compared to estimate how different factors impact respondent's WTP for protection.

Methods are outlined in section 2, including a description of the survey and econometric specifications. Results are provided in section 3, including descriptive statistics and econometric results. Discussions and conclusion are provided in section 4.

2. Methods

The methodology section is broken into two main sub-sections. The survey is discussed in section 2.1. This includes an overview of the study region, a detailed description of the survey structure, including the WTP question and a summary of survey data, and an overview of bias reduction measures. Section 2.2 outlines the econometric methods that are used to analyze the survey data, including OLS, Heckman two-step and Tobit Interval models. Fig. 1 provides a flowchart of the methods used in this study.

2.1. Survey

2.1.1. Flood region

HRM is a county in Nova Scotia, Canada that spans an area of roughly 5500 km^2, and has a regional population of more than 400,000 (Statistics Canada, 2016), most of which are in the city of Halifax. HRM is bordered to the south by the Atlantic Ocean (See Fig. 2). The city of Halifax is home to a large sea-port, and has considerable infrastructure near the water, as well as waterfront homes and businesses in the downtown region.

The region has historically experienced damage from flooding due to relatively small, frequent storms. However, Hurricane Juan, the 2003 winter storm that has been categorized as a 1–100 year event, reached sustained wind speeds of 160 km/h and coastal surge of 4.9 feet above normal tides (NOAA, 2003). Hurricane Juan caused loss of life, wide spread power outages and extensive flooding of coastal homes. Rough estimates of the damage done during Juan exceeded C$200 million (Charles and Wells, 2011). Future damages could increase if storms such as Juan become more frequent and intense due to climate change (NS Government, 2009; Forbes et al., 2009; AGRG, 2017).

Feltmate (2015) ranks Halifax 15th out of 15 Canadian cities, in terms of preparedness for reducing flood related damage. Currently, all three levels of government in NS are conducting research on SLR and storm surge, including flood mapping and environmental forecasts. While the government has identified the need for protection, no significant policies or programs have been undertaken, nor does legislation exist for coastal protection (NS Government, 2009, 2018). The results of this survey will therefore inform policy aimed at mitigating potential damage from storms in HRM, and also be useful for policy makers in other jurisdictions that face similar challenges.

2.1.2. Structure of the survey

The survey was designed to determine individual's WTP to protect against damages associated with SLR and storm surge in HRM under a changing climate. The survey begins with a discussion of the impact of flooding damages from coastal storms in HRM. Participants are told that the survey focuses only on WTP to protect against flooding and erosion from SLR and storm surge, and that damages from wind gusts should be ignored. The focus of the study is on flooding, as this could theoretically be mitigated via a sea-wall, whereas wind damages are harder to protect against.

The initial survey questions attempt to capture individual's perception of risk, which may affect WTP for protection. Participants are asked how often they expect to be flooded. Questions are then asked to capture individual's level of concern related to different potential risks (fire, flooding, terrorism, etc.).

In the second section, a coastal management scenario is introduced. It is assumed that a theoretical program (i.e., a sea wall) could offer full protection from flooding related to storm surge for the next 100 years in HRM. Respondents were told that a storm as severe as Hurricane Juan would occur every 100 years without climate change. While Juan is the most recognizable storm, participants are told to consider that protection will mitigate damages from all storms. Respondents are asked to state their WTP for protection, using the payment card method. Details about the payment mechanism are provided in the survey:

"Suppose the protection program were to be implemented by government. Given that this program would provide 100% protection from storm surge damages, for all potential storms, what is the most you would pay per month for protection?

This study assumes that the cost would be paid through an increase in your annual property taxes (if you rent your residence, you can assume that the cost to you would be an increase in your rent over the month). Assume that this monthly payment will be made for the next 10 years"

$0	$1	$2	$5	$10	$20	$40
$60	$80	$100	$200	> $200	Don't know	

As outlined in Haile and Slangen (2009), the payment-card method, which allows respondents to simply choose a WTP value, is useful as it avoids the starting point bias that may exist in bidding games and many problems associated with open ended questions, and is a more efficient form of sequential bidding. However, the approach is limited relative to the double-bounded dichotomous choice method, which allows for

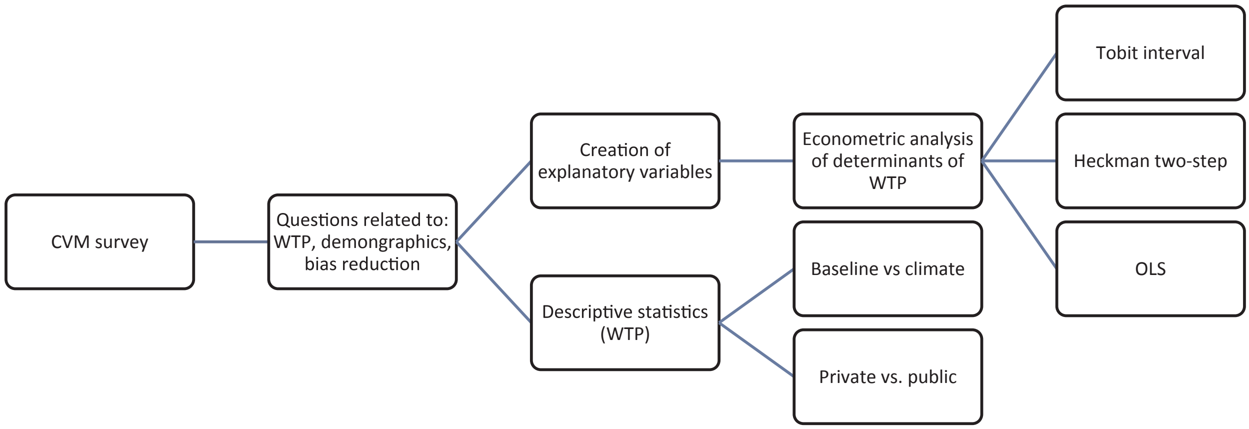

Fig. 1. Overview of methods.

negative WTP values.

Climate change is introduced in the third section of the survey. Respondents are asked to assume that climate change in this context implies doubling the frequency of all storm types. While it is difficult to know exactly how storms will change in HRM, this approach allows respondents to consider that things will worsen due to climate change, and the specific approach follows other studies in the literature (Botzen et al., 2009). Following this discussion of climate change, the WTP question is repeated. Respondents are also asked to consider the proportion of their WTP that would be spent to decrease private damages vs. public infrastructure.

The fourth and final section of the survey asks general questions that capture characteristics of the respondents, including their level of flood risk (based on elevation of home, distance from water, flood experience, etc.) and demographic factors.

2.1.3. Variables

The variables that were constructed to be used for statistical analysis of factors affecting individual's WTP for protection are presented in Table 1.

The first section of Table 1 captures individual's perceptions of risk. With the exception of *ConcernAvg*, each of these variables is a dummy variable based on a yes/no answer. For *ConcernAvg*, individuals were asked to state, on a scale from 1 to 5, their level of concern regarding how various potential risks might impact them personally. The variable constructed in Table 1 represents the average value across all questions, where 1 is less concerned.

Many of the variables included in Table 1 were constructed from the survey data. For instance, education and income had seven categories in the survey. In each case, seven binary variables were constructed for the purpose of statistical analysis. Simple high/low income and home value dummy variables were also created, based on assumed thresholds, which are presented in Table 1. The same process was followed for distance and elevation data.

2.1.4. Bias reduction

There are several concerns related to obtaining unbiased estimates of individual's WTP in CVM surveys (Arrow et al., 1993). Many of the potential biases associated with CVM surveys are outlined in Lantz et al. (2012) and include protest votes and 'yea-saying', when respondents strategically state a WTP rather than stating how much they would (and could) actually pay. A great deal of literature has focused on understanding and reducing hypothetical bias, where survey responses do not represent true WTP. Recent reviews of the literature indicate that the WTP estimated in CVM studies can be as much as two to three times actual WTP in markets (List and Gallet, 2001; Loomis, 2011, 2014; Harrison and Rutström, 2008). Several studies, including Aadland and Caplan (2003), have demonstrated that including a "cheap talk" script,

Fig. 2. Halifax Regional Municipality (Source: generated in the software Cartovista).

Table 1
Flood risk and demographic variables.

Category	*Variable*	*Description*
Risk	ConcernAVG	Average value of questions related to risk aversion. Each question was a categorical variable (for each risk, 1 = not concerned at all and 5 = very concerned).
	NegEffectsCC	Categorical variable. Created dummy variable 1 = agree or strongly agree that climate change will have significant negative effects in HRM over next 50 years
	FloodAwareness	Dummy variable. 1 = aware of flooding risks in HRM before survey
Elevation: Categorical variable divided in two groups	LowLying	Less than 10 m above ocean
	HighLying	More than 20 m above ocean
Distance: Categorical variable divided into two groups	NearOcean	Less than 5 km away from ocean
	FarFromOcean	10 or more km's away from ocean
	Waterfront	Dummy variable = 1 if individual owns waterfront property
Flood Return Period: Categorical variable, divided into three groups	ExpFloodOften	Expect house to flood every 1–10 years
	ExpFloodSometimes	Expect house to flood every 10–50 years
	ExpFloodNever	Never expect house to flood
Demographic	Rent	Categorical variable. Created dummy variable, 1 = renting current home
	Adults	Continuous variable: Number of adults living in house
	Business owner	Dummy variable = 1 if a business owner
	Married	Categorical variable for marital status, created dummy variable = 1 if the respondent is married
	HouseholdSize	Continuous variable: number living in home
Education: Categorical variable	University	Graduated with university degree (graduate or undergraduate)
	College	Graduated with college degree
	SomePSE	Has done some University/College/Tech School
	HighSchool	Has high school diploma or less
Income: Categorical variable divided into two groups	LowIncome	Less than 50,000$ household income
	HighIncome	More than 100,000$ household income
	Age	Continuous variable: Exact value
	Female	Dummy variable = 1 if female

which involves highlighting the hypothetical bias problem before participants make any decisions, may mitigate this bias. However, results in this literature are mixed (Champ et al., 2009; Aadland and Caplan, 2006).

This study follows Lantz et al. (2012) to reduce biases such as those described above. Specifically, a script is provided, similar to a cheap talk script, which reminds individuals to consider their budget constraints, and the effect of higher taxes each month on their lives. The survey also highlights that it is important that individual's answers represent their true preferences. Further, protest votes or yea-sayers were identified using follow-up questions to the WTP question. As an example, the following question was added to the survey, following each WTP question:

"If you are not willing to pay for the protection program (if you chose $0), please select why (please choose one):

1. I can't afford it
2. I don't consider flooding or damages due to storm surge to be a concern to me
3. I don't consider flooding or damages due to storm surge to be a concern in HRM
4. I do not have enough information to make this decision
5. Insurance should cover it
6. I do not believe the program will work
7. I think tax money could be better spent on other issues
8. I don't trust government to implement the program
9. I believe there will be negative consequences of the protection (environmental, etc.)
10. Other (Please specify)"

The third, sixth and eight responses would imply a protest vote. It is explicitly stated in the survey that respondents should assume that government would be able to undertake the project, and that the sea wall would be effective in mitigating all damages.

Yea-saying is the opposite of protest votes, where respondents state a higher WTP than they can afford or answer strategically in order to support the initiative. "Yea-sayers" were removed from the survey using a similar method; the following question was asked when positive values were given in the WTP question, and number 3 and 5 represent yea-saying:

"What is the most important reason why you are willing to pay for the protection program?

1. I think this is a small amount to pay for the benefits received to society
2. I might be directly impacted by flooding or damages due to storm surge
3. I think we should protect against flooding due to storm surge regardless of the cost
4. It is important to invest in protection against coastal storms for future generations
5. I feel it is the "right" thing to do
6. I think that our government does not do enough to protect against coastal storms
7. Other (Please specify) "

2.1.5. Survey administration and pre-test

The survey administration was contracted to Ipsos, a company that specializes in survey management and data collection (Ipsos, 2018), who used an online format with citizens of HRM. A major reason for this approach was the ease of implementation, and the fact that we could be guaranteed a certain amount of completed responses. Several rounds of pretesting were conducted before doing a full launch. There were 253 completed responses from two 'waves' of pre-test surveys taken from December 2015–February 2016. The main change following the first wave of 100 pre-test observations was that the survey stated

that monthly payments will exist for 10 years in the full sample, whereas the duration was not initially specified. There were no changes made after the second wave, and the full survey consisted of 1000 respondents in HRM.

2.2. Econometric specifications

2.2.1. OLS model

This study relies on statistical analysis to determine which variables (from Table 1) impact individual's WTP for protection from flooding due to storm surge, and by how much. The basic model is as follows:

$$WTP_i^{PC} = x_i\beta + \varepsilon_i y_i = x_i\beta + \varepsilon_i \tag{1}$$

where WTP_i^{PC} is the WTP value specified in payment card in the survey, i is an individual, x_i is a vector of explanatory variables and ε_i is the error term, which is assumed to be normally distributed with mean 0 and variance equal to 1. After eliminating protest votes and yea-sayers, two separate equations were estimated using OLS, in which the WTP in the baseline scenario and WTP in the climate change scenario served as dependent variables, respectively. However, there may be several issues with estimates from the OLS model, due to potential sample selection bias and censored data, so Heckman two-step and Tobit models were considered as well.

2.2.2. Heckman two-step model

Several respondents in a CVM survey will state that their WTP is zero. Some of these individuals may have a true zero WTP, while others may be a protest vote. Including protest votes in the model may bias WTP estimates downward. As discussed above, the survey structure allows one to identify and remove protest votes and estimate WTP with the smaller sample using OLS. However, this will necessary exclude potentially relevant information.

An alternative to removing protest votes is to use the full sample and a sample selection model such as the Heckman two-step model (Heckman, 1976, 1979) to correct bias associated with sample selection. Sample selection bias may be an issue due to self-selection by the individuals being considered (Heckman, 1979). This may be an issue in the context of protest votes, since these individuals are self-selecting out of the sample and 'missing' from the data; their true WTP may be positive but they choose a zero WTP value for other reasons (protest).

A Heckman two-step model was considered and the results were compared to the OLS regression with protest votes removed. The Heckman model corrects sample selection bias by adjusting the regression model for the probability of protesting. The WTP value is measured in a two-step process. In the first stage, a Probit model is used to model the decision of respondents to pay or not:

$$Z_i^* = x_{pi}\beta + \varepsilon_{pi} \tag{2}$$

$$Z_i = \begin{Bmatrix} 1 \; if \; x_{pi}\beta + \varepsilon_{pi} > 0 \\ 0 \; if \; x_{pi}\beta + \varepsilon_{pi} \leq 0 \end{Bmatrix} \tag{3}$$

The first stage of the model is called the selection equation. Z_i^* is an unobserved (estimated) variable measuring the probability that an individual is willing to pay, whereas Z_i is a binary variable that takes a value of 1 if WTP > 0, and 0 otherwise. In the second stage, the outcome equation is estimated using OLS:

$$WTP_i^* = x_{oi}\beta + \rho\sigma\lambda(x_{pi}\beta) + \varepsilon_{oi} \tag{4}$$

WTP_i^* represents the amount that respondents chose to pay, but WTP_i^* is only observed if $Z_i = 1$. In this model, x_{pi} *and* x_{oi} are vectors of explanatory variables and the $\beta's$ are the unknown coefficients. ε_{oi} *and* ε_{pi} are assumed to have a bivariate Normal distribution, with mean 0 and standard deviation equal 1. The correlation coefficient between ε_{oi} *and* ε_{pi} is equal to ρ. If $\rho = 0$, then the error terms are independent and the two equations can be estimated separately (Heckman, 1976, 1979).

To account for selection bias, the outcome equation in (4) includes the term $\rho\sigma\lambda(x_{pi}\beta)$, where ρ is an unknown coefficient to be estimated, σ is the standard deviation and λ is the inverse Mills ratio, which is constructed from the Probit model in (2):

$$\lambda(x_{pi}\beta) = \frac{\phi(x_{pi}\beta)}{\Phi(x_{pi}\beta)}$$

where ϕ and Φ are the standard Normal density and standard Normal functions, respectively (Heckman, 1979). The inclusion of this variable in the OLS model corrects for selection bias, providing consistent estimates of WTP. If the estimated value of ρ is statistically different than zero, then the residuals of the selection and outcome equations are correlated, and there is evidence of sample selection in the model (Fonta et al., 2010).

Notice that the explanatory variables x_{owi} and x_{pi} may be the same. However, to improve identification, one can include additional explanatory variables in the selection equation that are correlated with Z but uncorrelated with WTP. That is, they affect selection but not the outcome (Sartori, 2003). In the current case, the variable *FloodAwareness* fits this criterion, since based on simple regressions, the variable is found to be correlated with an individual's decision to choose a positive WTP value but is not correlated with the value of WTP. *FloodAwareness* is therefore included in the selection but not the outcome equation.

2.2.3. Tobit model

A second issue with OLS in the current context arises due to the nature of the data from the payment card. The data are censored at zero, since one cannot observe negative WTP values. The Tobit model is typically used to deal with left censored data (Tobin, 1958). Further, the data are also interval censored in this model. Respondents are asked how much they are willing to pay in dollars and give several options to choose from. As an example, if they choose $10 from the payment card, they are willing to pay $10 but not $20. One cannot know if they are willing to pay any value between $10–20, so their WTP falls within the interval $10–20. Given left censored and interval censored data, a Tobit Interval regression model is employed to model determinants of WTP (Botzen and van den Bergh, 2012). The determinants of WTP are analyzed using OLS, Heckman two-step and Tobit Interval models. A comparison of the results from these models will determine consistency of parameter estimates.

3. Results

3.1. Summary of survey data

3.1.1. WTP values

Upon removal of what were deemed to be biased observations ("yea-sayers" or protest votes), 123 out of a total of 810 observations were removed from consideration. There were only 810 initial observations since incomplete surveys were removed from the sample, where individuals did not answer all questions in the survey. This includes individuals that stated that they 'did not know' how much they were willing to pay. Of the 810 observations that were considered, 582 individuals stated that they had a positive WTP for protection in HRM in the baseline scenario. Table 2 summarizes WTP values for the entire sample, before and after removal of biased values. Table 2 also provides WTP values for the sample excluding the first 100 observations form the pre-test.

Removal of the 123 'biased' observations did not significantly impact the WTP averages, compared to the full data set. Further, WTP is higher in the full sample compared to the pre-test sample. Overall, WTP in the climate change scenario is slightly higher than the baseline scenario, given the more significant threat. This is consistent across sub-

Table 2
Willingness to pay for protection in HRM.

Variable	Observations	Mean	St. Dev.	Median	Min	Max
Without Climate Change:						
WTP before bias removal	810	11.93	21.29	5	0	> 200
WTP after bias removal	687	11.77	18.63	5	0	100
WTP before bias removal, excluding pre-test	720	12.31	22.09	5	0	> 200
With Climate Change (cc):						
WTPcc before bias removal	810	13.18	24.68	5	0	> 200
WTPcc after bias removal	687	13.45	24.07	5	0	> 200
WTPcc before bias removal, excluding pre-test	720	13.66	24.94	5	0	> 200

samples of the data. A *t*-test of the means in the baseline and climate change scenarios (full sample) indicate that one can reject the null hypothesis that the means are equal at 1% significance level. Overall, the value of WTP is similar to the value of 7.85€ −12.90€ per month found in Botzen and van den Bergh (2012) for a scenario without climate change.

The WTP means presented in Table 1 can be thought of as conservative estimates, as they are consistent with the lower bound of the non-parametric Turnbull estimate (Haab and McConnell, 2003). If an individual stated that they are willing to pay $10 per month, then they are willing to pay $10 per month but not $20, but their WTP may be between $10 and $20. By taking the mean using the value provided in the payment card ($10 in this example), a lower bound of overall WTP is estimated.

3.1.2. Personal and public trade-off

Given that there is a great deal of public infrastructure in HRM, and that not all citizens of HRM will be impacted by storm surge, participants were asked to state what percent of their WTP value is to protect against their personal damages vs. damages to others (including damages to public infrastructure, other people's homes, or other non-market damages such as clean up time). A follow up table also asked them to rank which services they would most like to protect. Overall, 58% of the WTP values were to protect against damages to others (including public goods), with 42% of the WTP values to protect against personal damage. Further, of the categories listed in Table 3, individuals were most often WTP to protect against damages to public infrastructure, as well as power outages.

3.1.3. Explanatory variables

Information on explanatory variables is provided in Table 4; the table includes mean values for continuous variables, and the proportion of the sample that falls into the given category for dummy and categorical variables. All variables that were included in the final regression are reported in Table 4. The values from the survey sample are compared to the HRM population, based on 2016 census data (Statistics Canada, 2016).

More than half the survey sample was married, and very few individuals lived in waterfront property. More than a third of the survey population had a university degree, relative to having a college degree, high school degree or neither. The majority of the survey population

Table 3
Ranking of private and public goods that participants would pay for (1 = most willing to pay).

	Average rank (1–6)
Physical damage to home/business	2.89
Physical damage to public goods	4.01
Public infrastructure	2.53
Lost leisure or recreation time	5.15
Power outages	2.50
Environmental factors, beaches/marshes	3.89

Table 4
Values of explanatory variables.

Variable	Mean value	Percent (based on a total sample of 810)	Percent in HRM population
ConcernAVG	2.65		
Waterfront		6.4	
Female		51.6	52
Pre-test		11.1	
Married		58.3	45
Age	46.45		40.8
Rent		35.4	40
University (BA or above)		37.6	29
ExpectFloodOften		18.4	
NegEffectsCC		70.2	
Business owner		4.3	9[a]
Income under 30,000		14.1	18.1
Income 30,00–50,000		20.8	17.1
Income 50,000–70,000		17.5	15.2
Income 70,000–100,000		22.5	18.8
Income 100,000–150,000		17.8	18
Income over 150,000		7.3	12.8

[a] Self employed.

believed that climate change would pose threats in the region, whereas only 18.4% believed they would be flooded as often as every 10 years. For comparison, 40.3% believed that they would never be flooded. Overall, the data from the sample was very similar to HRM census data. However, the most noticeable differences are that the survey sample is more highly educated, and more individuals reported being married.

3.2. Econometric results

Table 5 compares results from the OLS, Heckman two-step and Tobit Interval models using the explanatory variables in Table 4. All models were estimated in Stata (version 14). The variables included in the model were those that were statistically significant, as well as demographic variables such as income and education that one might expect would have an impact on WTP. Certain variables were removed due to concerns about multi-colinearity (i.e., waterfront and distance to coast). Several non-linear terms were considered, such as age squared, or rent*age, but no interaction terms were found to be significant.

All models were estimated using Huber-White robust standard errors, to account for potential heteroskedasticity (Huber, 1967; White, 1980). For the OLS and Tobit models, there were 687 observations for the WTP variable after removal of biased observations, but only 588 observations in all models when income variables are included, since some individuals chose ‘prefer not to answer’ for that question. For the Heckman model, there were 690 final observations, since all observations that had a zero WTP were included for this model to test for sample selection (protest votes were not removed).

When comparing results across models, several trends are apparent. There is no evidence of sample selection bias in the model specified, given that the coefficient on the inverse Mills ratio in the Heckman model is insignificant. The results are also consistent across models, in terms of sign and significance of coefficients. The magnitude of the

Table 5
Results of multivariate regression analysis of willingness to pay.

	Baseline				Climate Change			
	OLS	Heckman		Tobit Interval	OLS	Heckman		Tobit Interval
		Probit	OLS			Probit	OLS	
Constant	1.60	−0.24	2.42	−4.64	1.11	−0.03	3.75	−6.59
ConcernAVG	2.91***	0.19***	3.49**	4.57***	5.75***	0.16**	6.60***	7.68***
ExpectFloodOften	8.27***	0.49***	8.51***	11.61***	8.36**	0.37**	8.51**	12.03***
Waterfront	7.87**	0.19	12.23***	9.22*	4.77	0.22	4.76	6.75
Age	−0.06	-.15***	−0.08	−0.16**	−0.12	−0.01**	−0.12	−0.20**
NegEffectsCC	3.21**	0.48***	3.82	7.22***	4.24**	0.48***	4.01	9.65***
Pre-test	−3.84**	0.15	−6.00*	−3.70	−5.01**	0.05	−6.54*	−5.91*
Rent	5.13**	0.07	5.96**	6.46**	6.51**	0.02	7.70**	7.99**
Female	−3.22**	0.12	−4.40*	−2.48	−4.85**	0.22*	−6.88**	−3.99
Business owner	−5.75**	−0.22	1.07	−9.00**	−3.43	−0.07	−3.40	−4.70
Married	2.88*	0.07	2.90	3.35	1.97	0.02	1.84	2.03
University	−1.03	0.14	−1.96	−0.55	0.8	0.14	0.88	1.31
Income < 30,000	−1.29	0.29	−3.05	−1.01	−2.49	0.03	−4.46	−3.71
Income 30,000–50,000	1.32	0.07	4.14	1.12	−2.54	0.02	−4.26	−3.50
Income 50,000–70,000	1.54	0.31	2.90	2.56	−4.30	0.09	−7.40	−4.71
Income 70,000–100,000	−0.34	0.27	−1.77	1.57	−3.49	0.22	−5.75	−2.14
Income 100,000–150,000	1.59	0.31	1.40	3.82	−1.05	0.31	−3.48	0.76
FloodAwareness		0.33**				0.22		
Mills Ratio			5.02				4.4	
N	588	690	690	588	588	690	690	588

The asterisks denote significance: * for 10%, ** for 5% and *** for 1% significance respectively.

estimates does vary across models, but not significantly. It is therefore not surprising that the WTP values estimated from the models are comparable. The mean WTP value from the data was 11.93, whereas the estimated WTP values (predicted values from the regression models, at mean values) from the OLS, Heckman and Tobit models were 12.15, 14.08 and 11.81, respectively. The respective standard deviations were 6.26, 7.79 and 9.47.

The remainder of this section discusses the variables that impact WTP, focusing primarily on results from the Tobit Interval model. Since there is no evidence of selection bias, the Tobit Interval model is the appropriate model to use for left censored and interval censored data (Botzen and van den Bergh, 2012).

3.2.1. Significant variables

Several variables had a significant effect in all of the models considered. *ConcernAVG* has a positive and significant impact in all models, which indicates that the more concerned an individual is about risky events, the higher the WTP. Further, if individuals expect to be flooded often (at least every ten years), their WTP increases by $11.61 per month (in the baseline Tobit model) relative to individuals that do not expect to be flooded that often. Other studies have created similar indices that were significant (Zhai et al., 2006; Botzen and van den Bergh, 2012). *NegEffectsCC* also has a positive and significant impact on WTP: if individuals believe that climate change will cause significant damages in HRM, they are willing to pay $7.22 more per month than those that do not believe climate change will lead to negative impacts, all else equal. Perceptions of climate change seem to influence WTP, even in models where respondents were told to assume no climate effects.

Other variables had impacts in some models but not others. *Waterfront* has a positive and significant effect in the WTP model without climate change, but the effect is not significant with climate change. The pre-test variable is also significant in the OLS models but not the Heckman or Tobit models. From the Tobit model, business owners were willing to pay $9.00 per month less than non-business owners, those who rent were willing to pay $6.46 per month more than homeowners, and males were willing to pay $2.48 per month more than females. These results were significant in most models. The WTP value and likelihood that WTP was positive both decreased with age in some but not all models.

While some demographic variables had a significant impact in certain models, there was no evidence in any of the models to suggest that education or income play a role in WTP. This is surprising, as one might expect that higher income (to a certain point) would increase WTP. To investigate the impact of income on WTP, six of the seven binary variables that were created for each of the income categories were included. All variables presented in Table 5 are therefore relative to the excluded variable, which was income over $150,000. Several different high/low dummy variables were also created with different income level cut offs in order to capture the impact of having low, middle or high annual income. All income variables had an insignificant impact on WTP in all models. Finally, the results suggest that having a University degree (BA or higher) does not impact WTP values.

3.2.2. Baseline vs. climate change

The results are very similar in the baseline vs. climate change Tobit models, although there are a few differences. The marginal effect of a higher 'concern average' on WTP is higher in the climate change regression, which is intuitive. More concerned individuals will be willing to pay more in an uncertain but potentially more damaging future environment. The *Waterfront* variable has an impact on WTP in the baseline model but not the climate change regression, as stated above. Business owners have a significantly smaller WTP in the baseline model, but this result is not significant in the climate change model. Results of the Heckman models are very consistent in the baseline and climate change models.

3.2.3. Results in the context of the literature

The results of the regression models can be compared to other studies in the literature. Zhai et al. (2006) found that flood experience, distance from the river, and income per capita of the region impacted the WTP values. The first two results are consistent with the results in this study, whereas the result related to income is not. Botzen and van den Bergh (2012) found that perceptions about climate change, risk aversion, geographic variables and demographic variables such as gender, age, education and income all have a statistically significant impact on WTP. Botzen et al. (2009) found that WTP for sandbags used for mitigation was positively impacted by risk aversion, as well as geographic location (close to the river) and knowledge about floods but was not impacted by demographic variables such as age, gender and

income. These results are consistent with the results in the current study.

4. Discussion and conclusion

This study used CVM to examine individual's WTP for protection from damages associated with flooding related to SLR and storm-surge in HRM, Canada, in the context of climate change. The novel contribution of this study is the application of the CVM method in a previously unstudied region to better understand WTP to avoid damage, and inform policy aimed at protecting against damage due to sea-level rise and storm surge. The main conclusions from the results of the survey are that there is broad monetary and vocal support for combating storm surge effects in HRM. Over two thirds of residents in the sample foresee negative effects associated with climate change, and more than 72% of respondents are willing to pay for protection. On average, WTP is roughly $12 per month over a ten-year period without the expectation of climate change, and roughly $13 per month assuming climate change will have negative impacts in the region.

Based on statistical analysis, the estimated value for WTP was similar from the OLS, Heckman and Tobit Interval models. While many demographic variables such as education and income are not statistically significant in explaining the WTP values, vulnerability to flooding, a belief that climate change will pose negative risks and concern related to risky events each have a positive and statistically significant impact on WTP. Generally, these results are consistent with studies in other developed nations, such as Japan (Zhai et al., 2006) and the Netherlands (Botzen and van den Bergh, 2012), in terms of the magnitude of the WTP value, as well as the variables that impact WTP.

This study provides a preliminary analysis of WTP in HRM and provides valuable information for policy makers considering options to mitigate damages associated with climate change and storm surge. There is clear support to protect against flooding due to storm surge in HRM, and an understanding among residents that this is a serious issue in the region. Further, based on WTP estimates, the benefits of protection from storm surge in HRM could potentially be very large. Whether or not protection from storm surge is economically feasible will depend on the costs of protection. Estimates from Darwin and Tol (2001) suggest that the costs of shoreline protection from sea-level rise will equal roughly $1 million per km in Canada. A more detailed examination of protection costs, including protection from storm surge, as well as a detailed cost-benefit analysis of protection are beyond the scope of this project and therefore left as future avenues of research.

Based on the results of the survey, there is uncertainty regarding who should pay for protection. Given that individuals with specific risk factors (like owning waterfront property) have a significantly higher WTP, public support for such projects may not be universal. The disparity in WTP for protection could also justify the establishment of flood insurance, or a risk-based payment scheme for adaptation, where dwellings most at risk pay a high amount towards the adaptation fund. However, while vulnerability to storm surge has a major statistical impact on WTP, when ranking public vs. private goods, most people said they are willing to pay to protect public goods or other people's property. Clearly, there is wide spread support for protection in HRM, even though many people don't believe they will be impacted directly. Finally, WTP does not change dramatically when climate change impacts are introduced, which suggest that this is an important issue to residents, whether or not conditions worsen in the coming years.

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References

Aadland, D., Caplan, A.J., 2006. Cheap talk reconsidered: new evidence from CVM. J. Econ. Behav. Organ. 60 (4), 562–578.
Aadland, D., Caplan, A.J., 2003. Willingness to pay for curbside recycling with detection and mitigation of hypothetical bias. Am. J. Agric. Econ. 85 (2), 492–502.
AGRG, 2017. Flood Risk Modeling of Halifax Harbour. Obtained online (May 6, 2017) at: http://agrg.cogs.nscc.ca/node/259.
Arrow, K., Solow, R., Portney, P.R., Leamer, E.E., Radner, R., Schuman, H., 1993. Report of the NOAA panel on contingent valuation. Fed. Regist. 58 (10), 4601–4614.
Bin, O., Kruse, J.B., Landry, C.E., 2008. Flood hazards, insurance rates, and amenities: evidence from the coastal housing market. J. Risk Insur. 75 (1), 63–82.
Bin, O., Landry, C.E., 2013. Changes in implicit flood risk premiums: empirical evidence from the housing market. J. Environ. Econ. Manag. 65 (3), 361–376.
Botzen, W.J., Aerts, J.C., van den Bergh, J.C., 2009. Willingness of homeowners to mitigate climate risk through insurance. Ecol. Econ. 68 (8), 2265–2277.
Botzen, W.W., van den Bergh, J.C., 2012. Risk attitudes to low-probability climate change risks: WTP for flood insurance. J. Econ. Behav. Organ. 82 (1), 151–166.
Brouwer, R., Bateman, I.J., 2005. Temporal stability and transferability of models of willingness to pay for flood control and wetland conservation. Water Resour. Res. 41 (3).
Brouwer, R., Langford, I.H., Bateman, I.J., Turner, R.K., 1999. A meta-analysis of wetland contingent valuation studies. Reg. Environ. Change 1 (1), 47–57.
Brouwer, R., Akter, S., Brander, L., Haque, E., 2009. Economic valuation of flood risk exposure and reduction in a severely flood prone developing country. Environ. Dev. Econ. 14 (3), 397–417.
Champ, P.A., Moore, R., Bishop, R.C., 2009. A comparison of approaches to mitigate hypothetical bias. Agric. Resour. Econ. Rev. 38 (2), 166–180.
Charles, J., Wells, R., 2011. Planning for Sea-Level Rise in Halifax Harbour. Obtained online at: https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/earthsciences/pdf/mun/pdf/halifax_e.pdf.
Church, J.A., Clark, P.U., 2013. Sea Level Change. (Chapter 13) of Climate Change; The physical Science Basis. IPCC Obtained online at. http://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_Chapter13_FINAL.pdf.
Clark, D.E., Novotny, V., Grifin, R., Booth, D., Bartosova, A., Daun, M.C., Hutchinson, M., 2002. Willingness to pay for flood and ecological risk reduction in an urban Watershed. Water Sci. Technol. 45 (9), 235–242.
Costanza, R., Pérez-Maqueo, O., Martinez, M.L., Sutton, P., Anderson, S.J., Mulder, K., 2008. The value of coastal wetlands for hurricane protection. AMBIO A J. Hum. Environ. 37 (4), 241–248.
Darwin, R., Tol, R.S.J., 2001. Estimates of the economic effects of sea level rise. Environ. Resour. Econ. 19 (2), 113–129.
Daun, M.C., Clark, D., 2000. Flood Risk and Contingent Valuation Willingness to Pay Studies: A Methodological Review and Applied Analysis. Technical Report No. 6. Institute for Urban Environmental Risk Management, Marquette University, Milwaukee, Wisconsin.
Farber, S., 1987. The value of coastal wetlands for protection of property against hurricane wind damage. J. Environ. Econ. Manag. 14 (2), 143–151.
Fankhauser, S., 1994. Protection vs. retreat – the economic costs of sea level rise. Environ. Plan. 27, 299–319.
Feltmate, B., 2015. Preparedness of Fifteen Canadian Cities to Limit Flood Damage. Cooperators Insurance group Retrieved online (August 15, 2016): http://www.cooperators.ca/en/about-us/about-sustainability/extreme-weather-and-insurance.aspx.
Fonta, W.M., Eme Ichoku, H., Kabubo-Mariara, J., 2010. The effect of protest zeros on estimates of willingness to pay in healthcare contingent valuation analysis. Appl. Health Econ. Health Policy 8 (4), 225–237.
Forbes, D.L., Manson, G.K., Charles, J., Thompson, K.R., Taylor, R.B., 2009. Halifax Harbour extreme water levels in the context of climate change: scenarios for a 100-year planning horizon. Geol. Surv. Canada 6346 (2009), 21 open file.
Ghanbarpour, M.R., Saravi, M.M., Salimi, S., 2014. Floodplain inundation analysis combined with contingent valuation: implications for sustainable flood risk management. Water Resour. Manag. 28 (9), 2491–2505.
Haile, D.T., Slangen, L., 2009. Estimating the willingness to pay for the benefit of AES using the contingent valuation method. J. Nat. Resour. Policy Res. 1 (2), 139–152.
Haab, T.C., McConnell, K.E., 2003. Valuing Environmental and Natural Resources: the Econometrics of Non-market Valuation. Edward Elgar Publishing, Northampton.
Harrison, G.W., Rutström, E.E., 2008. Experimental evidence on the existence of hypothetical bias in value elicitation methods. Handbook Exp. Econ. Result. 1, 752–767.
Heckman, J.J., 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In: Annals of Economic and Social Measurement, vol. 5. NBER, pp. 475–492 number 4.
Heckman, J., 1979. Sample bias as a specification error. Econometrica 47 (1), 153–162.
Huber, P.J., 1967. The behavior of maximum likelihood estimates under nonstandard conditions. In: Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, vol. 1. University of California Press, Berkeley, CA, pp. 221–233.
IPCC, 2013. Summary for policymakers. In: Climate Change 2013: the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
IPCC, 2007. Changes in Storm Surges, Flood Heights and Areas, and Waves. Obtained online at: https://www.ipcc.ch/publications_and_data/ar4/wg2/en/ch1s1-3-3-3.html.
Ipsos, 2018. Survey Management, Data Collection and Delivery. https://www.ipsos.com/

en-ca/survey-management-data-collection-delivery-ipsos-observer, Accessed date: 2 January 2019.
Kim, H., Son, J., Lee, S., Koop, S., van Leeuwen, K., Choi, Y.J., Park, J., 2018. Assessing urban water management sustainability of a megacity: case study of seoul, South Korea. Water 10, 682.
Lantz, V., Trenholm, R., Wilson, J., Richards, W., 2012. Assessing market and non-market costs of freshwater flooding due to climate change in the community of Fredericton, Eastern Canada. Clim. Change 110 (1–2), 347–372.
List, J.A., Gallet, C.A., 2001. What experimental protocol influence disparities between actual and hypothetical stated values? Environ. Resour. Econ. 20 (3), 241–254.
Loomis, J., 2011. What's to know about hypothetical bias in stated preference valuation studies? J. Econ. Surv. 25 (2), 363–370.
Loomis, J.B., 2014. 2013 WAEA keynote address: strategies for overcoming hypothetical bias in stated preference surveys. J. Agric. Resour. Econ. 34–46.
Markantonis, V., Meyer, V., Lienhoop, N., 2013. Evaluation of the environmental impacts of extreme floods in the Evros River basin using Contingent Valuation Method. Nat. Hazards 69 (3), 1535–1549.
NOAA, 2003. Tropical Cyclone Report Hurricane Juan. Obtained online at: https://www.nhc.noaa.gov/data/tcr/AL152003_Juan.pdf.
Nova Scotia (NS) Government, 2009. Sea Level Rise and Storm Events: the 2009 State of Nova Scotia's Coast Report. Obtained online at: http://www.novascotia.ca/coast/documents/state-of-the-coast/WEB_SLRSE.pdf.
Nova Scotia (NS) Government, 2018. Coastal protection legislation. Obtained online at: https://novascotia.ca/coast/Coastal-Protection-Consultation-en.pdf.
Ng, W.S., Mendelsohn, R., 2006. The economic impact of sea-level rise on nonmarket lands in Singapore. AMBIO A J. Hum. Environ. 35 (6), 289–296.
Navrud, S., Huu Tuan, T., Duc Tinh, B., 2012. Estimating the welfare loss to households from natural disasters in developing countries: a contingent valuation study of flooding in Vietnam. Glob. Health Action 5 (1), 17609.
Sartori, A., 2003. An estimator for some binary-outcome selection models without exclusion restrictions. Polit. Anal. 11, 111–138.
Sepehri, A., Sarrafzadeh, M.H., 2018. Effect of nitrifiers community on fouling mitigation and nitrification efficiency in a membrane bioreactor. Chem. Eng. Process. Process Intensif. 128, 10–18.
Statistics Canada, 2016. Census Profiles, 2016, Halifax Regional Municipality. Obtained online at: http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/page.cfm?Lang=E&Geo1=CSD&Geo2=PR&Code2=01&Data=Count&SearchType=Begins&SearchPR=01&TABID=1&B1=All&Code1=1209034&SearchText=halifax.
Stern, N.H., 2007. The Economics of Climate Change: the Stern Review. Cambridge University press.
Tapsuwan, S., Cook, S., Moglia, M., 2018. Willingness to pay for rainwater tank features: a post-drought analysis of sydney water users. Water 10, 1199.
Thunberg, E.M., 1988. Willingness to Pay for Property and Nonproperty Flood Hazard Reduction Benefits: an Experiment Using Contingent Valuation Survey Method. Diss.. Virginia Polytechnic Institute and State University.
Tobin, J., 1958. Estimation of relationships for limited dependent variables. Econ.: J. Econ. Soc. 31, 24–36.
Tol, R.S.J., 2002. Estimates of the damage costs of climate change. Part 1: benchmark estimates. Environ. Resour. Econ. 21 (1), 47–73.
Tol, R.S., 2009. The economic effects of climate change. J. Econ. Perspect. 23 (2), 29–51.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–830.
Withey, P., Lantz, V.A., Ochuodho, T.O., 2016. Economic costs and impacts of climate-induced sea-level rise and storm surge in Canadian coastal provinces: a CGE approach. Appl. Econ. 48.1, 59–71.
Yohe, G., Schlesinger, M., 1998. Sea level change: the expected economic cost of protection or abandonment in the United States. Clim. Change 38, 447–472.
Zhai, G., Sato, T., Fukuzono, T., Ikeda, S., Yoshida, K., 2006. Willingness to pay for flood risk reduction and its determinants in Japan. J. Am. Water Resour. Assoc. 42 (4), 927–994.